

# **Knowledge Aided SAR Target Detection and Display Remap - Veridian's First-year KASSPER Progress and Plans**

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## **1 INTRODUCTION**

Veridian's KASSPER proposal, as accepted by DARPA and AFRL, included the following five tasks to be investigated over the nearly four-year program duration:

- SAR Autofocus
- SAR Target Detection
- SAR Image Enhancement
- SAR Image Registration/Geolocation
- GMTI Target Detection

Under FY02 funding, during the period from April 2002 to November 2002, Veridian concentrated its KASSPER research on the areas of SAR target detection and SAR image enhancement via improved display remap. The plans for these activities were presented in a May 2002 program review. During the same period, Veridian devoted lesser effort to KASSPER approaches for moving target focusing and wind-blown tree-smear removal.

Veridian's FY02 KASSPER activities are summarized in Section 2 of this report. Recommended activities for FY03 are presented in Section 3.

## **FY02 ACTIVITY**

Veridian's FY02 KASSPER activities were concentrated on SAR stationary target detection and image remap. These topics were selected because it was felt that they offered significant pay-off from the application of KASSPER knowledge-aided approaches and because they addressed KASSPER opportunities at both ends of the spectrum of external knowledge detail and performance sensitivity.

SAR stationary target detection has similar function and importance to GMTI target detection. SAR target detection is often thought of as a *back-end* process performed off-line at a remote ground station following imagery down-link. However, it is highly desirable that SAR target detection be performed on-board the SAR collection platform in real-time and, most importantly, with a high degree of confidence. Such a *front-end* exploitation capability would greatly enhance the utility of SAR sensors particularly given the large-area, fine-resolution stripmap collection modes of current and near-term operational SARs such as those on the Global Hawk UAV and the U-2 aircraft.

The need for image quality improvement to support human inspection and interpretation is a critical aspect of SAR data exploitation that is not germane to GMTI applications. Effective SAR image quality enhancement is most acute in those applications requiring on-board viewing of the data prior to subsequent military response as is the case for tactical aircraft such as the F-18 and JSF.

## 2.1 SAR Stationary Target Detection

Veridian's initial consideration of KASSPER approaches for improved SAR target detection yielded three "obvious" candidates:

- *Terrain delimitation* exploits external knowledge of ground slope, cover, moisture, accessibility, etc., to weight SAR target detection likelihoods based on the local terrain suitability for targets to be present.
- *SAR change detection* exploits previously acquired SAR images to suppress false alarms from target-like cultural clutter (buildings, fences, etc.). Pixel-level coherent or non-coherent change detection approaches use previously acquired SAR images to effectively suppress background clutter thereby reducing false alarms and enhancing the detectability of low contrast targets.
- Computationally efficient *constant false alarm rate* (CFAR) SAR target detection is used for initial target screening by comparing each SAR image pixel to statistics of the local background and declaring "target present" when a pixel under test is not consistent with the background statistics. The CFAR formulation requires that the local background be homogeneous to yield the desired false alarm rate. The most common CFAR implementation uses a fixed background region about the pixel under test and suffers the consequences of degraded target detection performance when the background is non-homogeneous. More complex CFAR algorithm deviants attempt to adaptively segment the image into homogeneous clutter regions prior to the implementation of the background consistency test. An "obvious" KASSPER approach is to implement a knowledge aided CFAR (KA-CFAR) algorithm in which the image segmentation is performed using external knowledge sources such as terrain categorization maps and digital elevation models (DEMs), including estimates of tree canopy heights.

SAR target detection performance improvements based on terrain delimitation and change detection approaches have been the subject of multiple past research and development efforts and, thus, did not seem to be promising areas for KASSPER innovations. KA-CFAR for SAR stationary target detection, although hardly innovative, is directly analogous to the research thrusts of other KASSPER program participants to develop improved GMTI target detection algorithms using external knowledge to overcome local "training" issues related to non-homogeneous background clutter. Based on the belief that KA-CFAR for SAR target detection offered the potential for significant performance improvement and that the overall KASSPER program should address the advantages and disadvantages of analogous knowledge aided approaches for improved SAR and GMTI target detection, Veridian conducted the analysis described below.

### 2.1.1 KA-CFAR SAR Target Detection Impact Study

To illustrate CFAR performance improvement due to *a priori* knowledge of the clutter boundaries, 200 simulated complex Gaussian SAR scenes were generated. Each scene, as depicted in Figure 1, consisted of areas covered by grass, tree, or both, i.e., tree overlay region. The relative RCS of the trees was set to be 5 dB higher than that of the grass. Targets with RCS 10dB higher than the trees were inserted at different locations along the grass/overlay boundary – some on the grass and some in the tree overlay.

With targets placed *on grass* along the overlay region, Figure 2 shows that KA-CFAR achieved an order of magnitude or better reduction in the false alarm rate. The false alarm rate in this plot pertains only to grass areas immediately adjacent to tree overlay regions. The KA-CFAR results are equivalent to

common CFAR performance for targets in the grass region but not near the overlay boundary. The degraded CFAR performance is due to the contamination of the background estimates in the grass region along the overlay boundary.

With targets placed *in the tree overlay* region along the grass boundary, Figure 3 shows that KA-CFAR performance was virtually identical to that of the common CFAR algorithm. The false alarm rate in this plot pertains only to tree overlay areas immediately adjacent to the grass regions. The KA-CFAR performance in Figure 3 is significantly poorer than that shown in Figure 2 due to the lower target-to-clutter ratio (TCR) in the overlay region. In this case common CFAR performance is limited by the low TCR; it is not significantly degraded by contamination of the local background estimates. (The background estimates in the overlay region along the grass boundary *are* contaminated by the inclusion of some lower RCS grass pixels.)

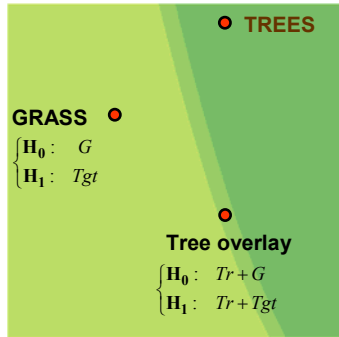


Figure 1. Simulated clutter regions observed by SAR.

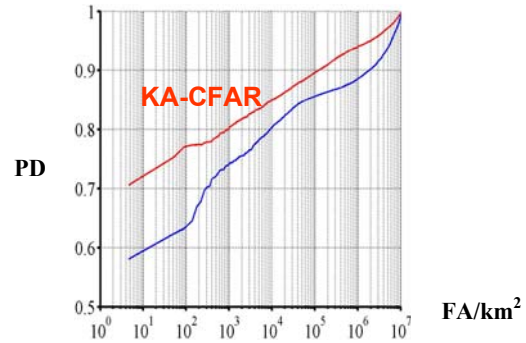


Figure 2. ROC for targets along the boundary *on grass* indicates a significant improvement using KA-CFAR.

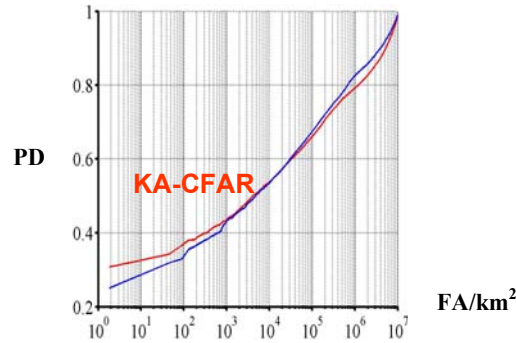


Figure 3. ROC for targets along the boundary *in the Overlay Region* indicates no KASSPER advantage due to low TCR.

The analysis results show that KA-CFAR performance can be significantly better than that of common CFAR in *some* situations. KA-CFAR will not yield improved performance for targets that are not near clutter boundaries. For targets near clutter boundaries, the performance improvement will increase as TCR decreases from high values, peaking at some intermediate TCR (a “sweet spot”), and becoming insignificant again as TCR becomes very low.

The practical utility of KA-CFAR is limited by its associated requirement for very detailed and accurate knowledge on clutter homogeneity and boundary locations. It is critical that a pixel under test be assigned to the correct clutter region so that it can be compared against the appropriate background statistics. In the simulations discussed above, KA-CFAR performance improvements would be reduced if pixels in the

grass along the grass/overlay boundary were compared against statistics of the overlay background region due to inaccuracies in the boundary location. SAR target detection is typically performed at resolutions on the order of one meter. Commensurately accurate knowledge of clutter boundary locations in SAR images imposes a considerable burden on the processes for generating the required ground cover information. Accurate projection of clutter boundaries in SAR images also requires precision digital elevation data not only for the ground but also for elevated cover classes such as trees and buildings.

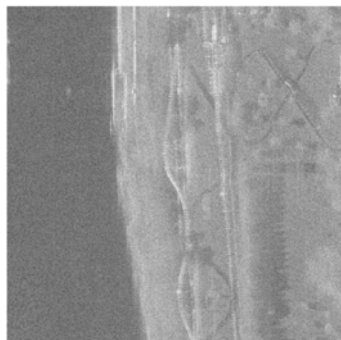
KA-CFAR utility is further limited by the need for external knowledge that correctly defines scene areas of homogeneous clutter. As mentioned above, common CFAR performance is degraded by contamination of the clutter background statistics. The same is true for KA-CFAR. This situation is particularly acute for designated homogeneous background areas that contain even a small percentage of high RCS cultural discretes.

## 2.2 SAR Image Remap

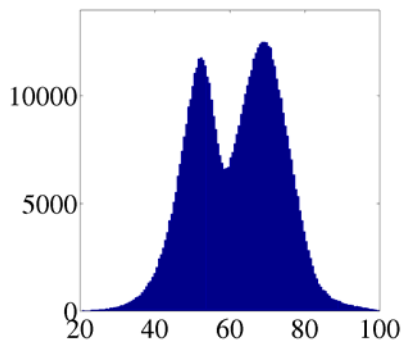
Current operational SAR systems rely on manual imagery interpretation by analysts/operators with widely varying levels of training and skill. SAR sensors typically produce uncalibrated imagery with 70dB dynamic range that must be interpreted using display devices limited to 30 dB dynamic range. Exploitation performance is highly dependent on the suitability of the remap function by which the imagery is compressed for display. The SAR image remap challenge is most acute in those military scenarios where the operators must examine very large amounts of data and/or must perform very quickly and, thus, do not have the luxury of “playing” with the remap parameters.

In support of a major operational SAR sensor, Veridian has developed and transitioned a SAR image remap selection algorithm (RSA-3) that adaptively produces 8-bit digital SAR imagery using a remap function whose parameters are set on the basis of global image statistics, i.e., it adapts to whole images.

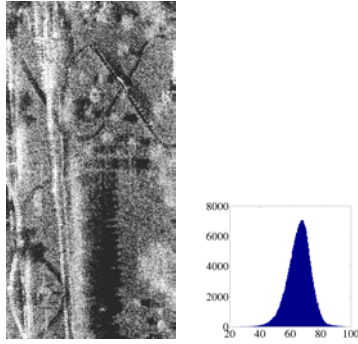
Figure 4 illustrates a log-magnitude SAR image and Figure 5 shows its associated histogram. The histogram is bimodal due to the presence of significant areas of land clutter (natural and cultural) and low RCS water return. The RSA-3 algorithm is known to perform very well when the SAR image is dominated by natural and cultural ground clutter (see Figure 6). As shown in Figure 7, the performance of the RSA-3 algorithm degrades when the image histogram becomes bimodal. RSA-3 performance shortfalls are typically observed in scenes along lake or ocean shorelines. Similar performance degradations occur in scenes with significant shadow areas. Terrain shadowing is particularly acute for airborne SAR sensors that operate at long-standoff ranges.



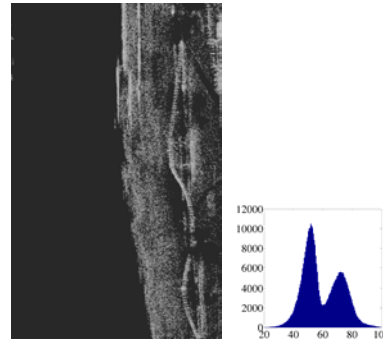
**Figure 4. Typical log-magnitude SAR Image (Boblo island, Detroit)**



**Figure 5. Histogram of magnitude image in Figure 4**



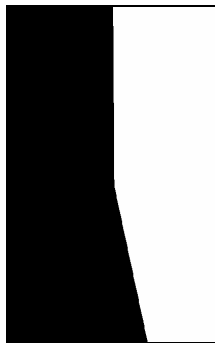
**Figure 6. RSA-3 remapping is excellent in the absence of areas of low return**



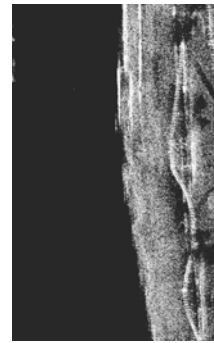
**Figure 7. As the areas of low return relatively grows, the quality of RSA-3 output diminishes**

Veridian is currently developing an enhanced non-KASSPER SAR image remap algorithm to address the bimodal histogram issue discussed above. The RSA-4 algorithm first attempts to automatically segment the image into land clutter and no-return areas. The entire image is then remapped exactly as in the RSA-3 algorithm except that the supporting statistics are determined only for the land clutter pixels.

Under this program, Veridian demonstrated a KASSPER SAR remap algorithm that is identical to RSA-4 except that external knowledge is used for the initial image segmentation. The result in Figure 9 was generated using the water/land (black/white) mask shown in Figure 8. It is greatly improved from the RSA-3 result in Figure 7.



**Figure 8. KASSPER water/land segmentation mask for image in Figure 9.**



**Figure 9. KASSPER SAR remap algorithm does not suffer from bimodal image histogram.**

In practice, the KASSPER SAR remap segmentation mask would be derived using land category knowledge (for water) and DEMs (for shadows). Clearly, the shadow masks must be based on the radar acquisition geometry. The KASSPER approach is concerned with no-return areas of substantial size and, thus, will perform well with a coarse segmentation mask (Figure 8). Likewise, its performance will be robust to substantial errors in the segmentation mask, particularly the inclusion of a significant fraction of no-return pixels (water or shadow) in the land area, because it is based on low-order statistics typically derived over a large sample set.

The KASSPER SAR remap algorithm is a viable alternative to the RSA-4 automated segmentation procedure. Automated segmentation is prone to error although the RSA-4 requirement is certainly at the low-end of the segmentation challenge-scale. The KASSPER SAR remap approach should have the

highest pay-off for tactical SAR sensors imaging relatively small scenes where small sample sizes may seriously degrade the automated segmentation results.

### **2.3 Moving Target Focusing and Wind-Blown Tree Smear Removal**

During FY02, Veridian devoted small-scale efforts to the consideration of KASSPER approaches for SAR moving target focusing and wind-blown tree smear removal. SAR moving target focusing is motivated by DARPA and DoD interest in precision engagement of moving and stationary targets. Focused SAR signatures of stationary targets are very useful for target recognition/identification. SAR signatures of moving targets are typically displaced from their true ground position and misfocused (smeared) in the cross-range dimension. GMTI radar is optimized for moving target detection and tracking but provides little capability for target identification. High-range resolution (HRR) radar imaging of moving targets provides some capability for moving target fingerprinting and identification but performance certainly does not approach that obtainable from focused 2-D SAR signatures.

Using moving target SAR data from its DCS radar testbed, Veridian has demonstrated computationally efficient approaches for focusing moving targets under purely translational motion. These techniques do not perform well when targets are moving along curved trajectories. The initial analysis conducted under this program indicates that external knowledge of the road on which a moving target is traveling would allow computationally efficient moving target focusing algorithms to perform well for the challenging cases of non-translational motion. Such capabilities would have a significant pay-off for precision targeting in complex environments.

Wind-blow trees can degrade interpretability of focused SAR target signatures that are contaminated by noise-like tree smears. The degree of contamination is determined by the tree RCS, the wind intensity, and the distance of the target from the offending trees. It is not particularly dependent on the SAR aperture time.

Veridian formulated a KASSPER approach for mitigating wind tree smear effects. The concept was to perform a spectral decomposition of a signature of interest and then to preserve a higher percentage of the prominent point returns as the distance increased between the target and the known tree locations. Figure 10 shows a sample image with moderately high degree of tree smears that extend over three stationary targets located on the road adjacent to the treelines. The prior knowledge of the roads (as possible target locations) allows significant processing gain for computationally expensive predictive methods such as MVM. Figure 11 illustrates the whole processed image that took several hours to process. The area of interest, shown by the red box, determines where MVM algorithm needs to be applied. This example shows a moderate level of smear reduction across the image, especially at the target chip size level.

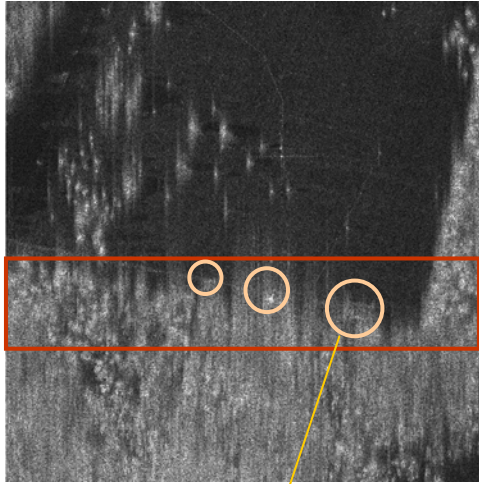


Figure 10. Tree-smearing image.

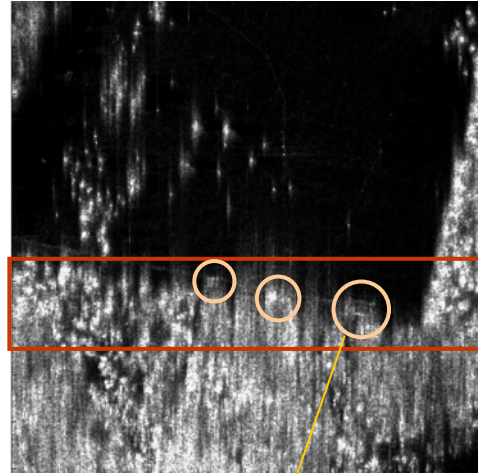


Figure 11. KA-MVM operates only in the relevant region of interest (red box).



## RECOMMENDED FY03 PLAN

We recommend that Veridian's FY03 KASSPER research concentrate on two topics: GMTI change detection and SAR moving target focusing. We believe that we can make significant progress on both subjects within the projected funding profile.

### 2.4 GMTI Change Detection

Our FY02 KASSPER effort on SAR stationary target detection has lead to the conclusion that change detection is the most productive approach for obtaining improved performance from the use of external knowledge sources. Veridian and other contractors/agencies have successfully demonstrated the benefits of SAR change detection in numerous applications. As such, we do not feel that it is a fruitful topic for near-term KASSPER innovations.

Instead, we recommend that Veridian leverage its expertise on SAR change detection to develop and demonstrate analogous GMTI approaches. GMTI change detection involves the simultaneous analysis of a *test* data set that may contain targets and a *reference* data set that does not contain targets or, at least, is assumed not to contain targets. From a KASSPER perspective, the reference data set is the requisite external information. To our knowledge, GMTI change detection has never been studied.

Using available dual and three-phase center moving target data from the Veridian DCS radar testbed, we will demonstrate the targeting performance benefits of GMTI change detection in comparison to a state-of-the-art single-acquisition (test data only) STAP approach. Of particular interest is the degree to which GMTI change detection can overcome STAP training issues related to background clutter inhomogeneity and contamination by other moving targets.

GMTI change detection will be pursued using non-adaptive GMTI test statistics, e.g., DPCA outputs. Fine-resolution, spotlight-mode, moving target DCS data will be processed into coarse-resolution GMTI test and reference data sets. This will allow us to study sensitivity to GMTI range/doppler resolution.

We will investigate both cell-level and object-level GMTI change detection. The former involves cell-level analysis of registered GMTI test and reference data sets and is analogous to pixel-level SAR change detection (coherent or non-coherent). Registration (warping and resampling) of the GMTI test and reference data sets will be performed using existing SAR image registration tools applied to the single-channel range/doppler data sets, i.e., the GMTI data before any clutter cancellation.

Object-level GMTI change detection involves analysis of moving target reports generated independently from the test and reference data sets and is analogous to SAR object-level change detection (OLCD). Its primary objective is false alarm reduction, i.e., cancellation of test data moving target reports if they are associated with reports generated from the reference data. As mentioned previously, the reference data is assumed to be devoid of moving targets but it is not assumed to be devoid of artifacts that are similar to moving targets.

In practice, cell-level GMTI change detection performance will be limited by the availability of reference data sets acquired at collection geometries that are similar to the test data collection. Object-level change detection is the next-best alternative provided that the less stringent test/reference report association can be handled properly. The spotlight-mode DCS data with typical 90 degree collection intervals about scene center will allow GMTI test and reference data sets to be generated with known aspect angle mismatches. We will use such data to quantify the performance trade-offs between these two complementary GMTI change detection approaches.

Under IR&D funding, Veridian has implemented a GMTI STAP algorithm specifically for use with the recently upgraded DCS testbed. Our GMTI change detection results will be compared against the outputs of this single-acquisition STAP approach.

## **2.5 SAR Moving Target Focusing**

We propose to implement a computationally efficient algorithm that will produce focused SAR signatures for moving targets with known trajectories. Using simulated moving target video phase history data, we will investigate the sensitivity of the algorithm to uncertainty in the target speed and errors in the external knowledge of the target path. We will demonstrate the algorithm using available DCS data of a military vehicle moving along a circle path.